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Reinforcing Fuzzy Rule-based Diagnosis of Turbomachines with Case-based Reasoning

M. Yang and Q. Shen

***Abstract*—** This paper presents an integrated knowledge-based system, which combines fuzzy rule-based reasoning with case-based reasoning, for turbomachinery diagnosis. By incorporating a case-based reasoning sub-system in a fuzzy rule-based system, the integrated system allows past experience to be applied in a more direct way. This helps improve the diagnostic accuracy of the rule-based system. This approach has been implemented for the specific task of identifying possible causes of observed vibrations in rotating machines, based on the initial work presented in [18]. The ability that the case-based sub-system brings to the integrated system in improving the diagnostic efficacy of the original rule-based system is demonstrated with test results on real cases.

I. Introduction

It has been well-recognised that the success of many industrial plants depends on the continued and safe operation of their rotating machinery (e.g., gas turbines, turbocompressors, and steam turbines). A fast and reliable identification of causes for observed vibration problems is highly desirable [18]. This is because an early diagnosis helps to avoid extensive damage to the machine and hence to reduce the downtime for repair which, in turn, helps improve productivity and economics.

Of course, it is natural for machines to have vibrations, in terms of motions of a machine or machine part back and forth from its rest position. However, if the vibration of a machine becomes excessive, some mechanical fault is usually the reason. Diagnosis by human inspection is simply too slow and costly for modern industrial plants. Automated monitoring and diagnostic systems are therefore necessary.

Having recognised the significance of applying intelligent techniques to aid finding faults in turbomachines, there have been many knowledge-based diagnostic systems developed in the literature. For example, the work of [15], [16] provided an initial expert system architecture for health monitoring and vibration diagnosis of turbomachinery. In this research, diagnosis is based on a combination of general fault matrix analysis, machine specific experience, and computer simulation. A similar approach is more recently reported in [17], supported with full implementation. This system aims at assisting plant operators in diagnosing the cause of abnormal vibration for rotating machinery. A decision table based on the cause-symptom matrix is used as a probabilistic method for diagnosing abnormal vibration. In addition, decision-tree based inductive learning [7] is adopted to obtain and represent diagnostic knowledge in a structured format.

There have been alternative approaches to conventional expert systems for monitoring and diagnosis of turbomachines. For instance, while treating diagnosis as a pattern classification task and based on the vibration characteristic spectrum, the approach proposed in [3] exploits the rough set theory [10] to facilitate diagnoses. In particular, it obtains accurate diagnostic results directly from a set of complete fault spectrum samples, and satisfactory diagnostic results from a set of incomplete fault spectrum samples. Also based on rough sets, a method for steam turbine-generator vibration fault diagnosis was proposed in [9]. This work applies the rough attribute reduction algorithm [12] to select the key features that will have the most significant impact upon the diagnostic classification process.

Although successful in their own targeted applications, aforementioned approaches do not explicitly address the particular problem in that the domain expertise in turbomachinery diagnosis usually includes vague concepts, such as "high" in the proposition "if the vibration at twice running speed is high, then the cause is misalignment". To exploit and maximise the use of such vaguely expressed knowledge and also imprecise measurements, a fuzzy rule-based diagnostic system has been proposed in [18], which is able to derive possibly inexact conclusions from inexact premises.

However, experimental studies have revealed an important limitation of this system: Although it may be able to identify possible vibration causes and even rank them as the most likely, there may be many such causes returned by the system from a consultation. Albeit multiple causes for vibration may be common in rotating machines, there would not normally exist a good number of them at the same time. If, however, past successful diagnostic cases have been recorded for the plant under monitoring or for a similar plant, the solutions found previously should be of positive assistance in differentiating the multiple possible diagnoses. Inspired by this observation and by the general understanding of the capability of case-based reasoning systems [4], [14], this paper presents an integrated approach to knowledge-based diagnosis of turbomachines via extending the existing fuzzy rule-based system with an incorporated case-based reasoning sub-system.

The rest of the paper is organised as follows. To be complete, a brief introduction to the fuzzy rule-based diagnostic system is given in section II. The integrated system is then outlined in section III. After that, a detailed account of the design of the case-based reasoning sub-system is presented in section IV. To demonstrate the effectiveness of the system, the results of typical experiments on real cases are reported in section V. Finally, the paper is concluded in section VI, with future directions of research pointed out.

II. Fuzzy Rule-based Diagnosis

The task of the fuzzy knowledge-based system described in [18] is to determine possible causes of a vibration problem and rank them according to their possibilities incrementally. The system produces an intermediate diagnostic result for each symptom presented by the user. It is also able to provide a what-if analysis facility, in order to help the user to investigate the impacts of potentially different symptoms upon the diagnostic result.

The diagnostic knowledge is extracted from Sohre's charts [11], which relate the subjective probability of the occurrence of a vibration symptom to an underlying cause. It is represented in a set of symptom-cause diagnostic rules and each of the diagnostic rules is of the following general form:

If Symptom is A then Cause is B

The following are two examples of such rules:

If direction of predominant amplitude is axial
then possible cause is initial unbalance

and

If predominant frequency is 1xRPM (high)
then possible cause is initial unbalance

Note that in the first example rule, the symptom of direction of predominant amplitude is fuzzy because its possible values "vertical" (V), "horizontal" (H) and "axial" (A) are vaguely defined concepts, as shown in Fig. 1. Also, in the second example rule, 1xRPM (high) means that the frequency 1-revolution-per-minute is predominant when its amplitude is considered to be high. Here, in common with general practice, the amplitudes of a frequency are described in one of the three fuzzy terms "high", "close to limit" and "low", as defined in Fig. 2.

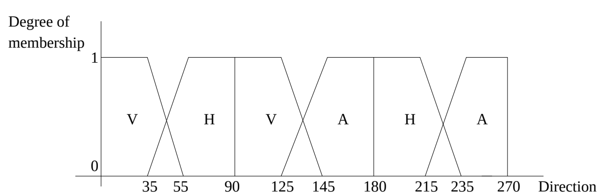

Fig. 1. Fuzzy sets for the direction of predominant amplitude of vibration

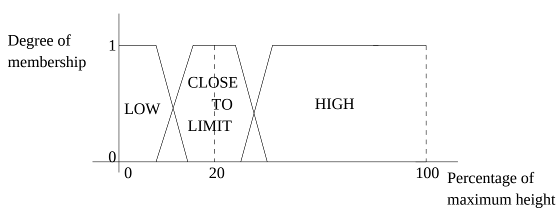

Fig. 2. Fuzzy sets for the terms "high", "close to limit" and "low" in the description of vibration amplitudes

The directly extracted rules as examplified above are obtained by treating different symptoms equally. In reality, different conditional attributes may have very different effects upon the derivation of a conclusion. By taking estimation of the relative degrees of dependency of a conclusion upon different conditional attributes, weights can be attached to individual rules to reflect their relative significance in deriving the same conclusion.

Computationally, the estimation of the dependency degrees is carried out via counting the number of times of those past successfully diagnosed cases, where the found cause did lead to the observed symptom, and that of the total past cases, where the same cause led to all of those different observed symptoms. That is, given a set of K directly derived rules of the form

$$R_j: \quad \textit{If Symptom is } A_j \textit{ then Cause is } B, \quad j = 1, 2, ..., K$$

the relative degree of dependency of B upon A_i is:

$$W_{R_j}(B, A_j) = \frac{\alpha_{A_j}}{\sum_{i=1}^{K} \alpha_{A_i}}, \qquad j \in \{1, 2, ..., K\}$$

where α_{A_i} stands for the count of the number of times in which attribute $A_i, i = 1, 2, ..., K$ is associated with the conclusion B. Denoting $W_{R_j}(B, A_j)$ by W_j for short, each of the weighted rules are then represented as follows:

$$R_j: \quad \textit{If Symptom is } A_j \textit{ then Cause is } B \quad (W_j)$$

The fuzzy rule-based diagnostic system works by performing forward chaining. This is because most of the facts about a vibration problem are given initially and as many as possible causes should be considered. A rule is fired if the observation and the value of the corresponding conditional attribute in the rule are of a certain similarity degree (i.e., partially matched between the underlying fuzzy sets, which are of course defined on the same universe of discourse). In this system, the technique reported in [1] is used to measure fuzzy set similarity S, based on the measure of possibility P and that of necessity N. In particular, given the fuzzy set associated with the condition, F_c, and the fuzzy set associated with the fact, F_f, the measure of similarity S is computed by

$$S = \begin{cases} P(F_c|F_f), & N(F_c|F_f) > 0.5 \\ (N(F_c|F_f) + 0.5) \times P(F_c|F_f), & \text{else} \end{cases}$$

where

$$P(F_c|F_f) = max(min(\mu_{F_c}(u), \mu_{F_f}(u))), \forall u \in U$$

(with U being the universe of discourse) and the measure of necessity N is defined by

$$N(F_c|F_f) = 1 - P(\neg F_c|F_f)$$

From this, when firing a rule, the weight of the conclusion is intuitively calculated as follows:

$$W_{conclusion} = W_{fact} \times W_{rule} \times S$$

where W_{fact} and W_{rule} have the obvious meanings of being the weight associated with the fact and that with the rule fired, respectively. In so doing, the higher the value of S, the more similar the fact to the condition value, and so the higher the weight of the conclusion. In particular, if the fuzzy set of the conditional attribute and that of the observation are identical, S will be equal to 1 and $W_{conclusion} = W_{fact} \times W_{rule}$.

If a deduced conclusion already exists, its weight is updated by the following:

$$W_{conclusion} = W_{new} + W_{old} - W_{new} \times W_{old}$$

This is also intuitive because the more evidence there exists which supports a conclusion, the higher is the significance of that conclusion.

The fuzzy rule-based diagnostic system has been shown to perform well for identifying a number of possible causes for observed symptoms in real settings. Conceptually speaking, it works by making a good use of (a) knowledge hidden in Sohre's charts, which are themselves derived from successfully solving real problems, and (b) ranking weights, which are again based on past experience. However, the system does not seem to have maximise the exploitation of information contained within previously resolved cases. This research intends to address this issue, in an effort to provide a more accurate diagnosis for newly presented vibration problem cases, by developing an integrated system that combines the existing fuzzy rule-based system and a case-based reasoning sub-system.

III. Overview of the Integrated System

As indicated previously, the integrated diagnostic system is designed to produce incrementally an immediate diagnostic result for each symptom presented by the user. Figure 3 shows the process of a consultation of the system. Given the symptoms associated with a vibration problem, the fuzzy rule-based sub-system applies a set of diagnostic rules to deduce all possible causes, whilst the case-based sub-system applies past experience directly to refine the solutions for the problem at hand. With the integration of these two sub-systems, the overall diagnostic system is able to provide reliable diagnoses for typical vibration problems.

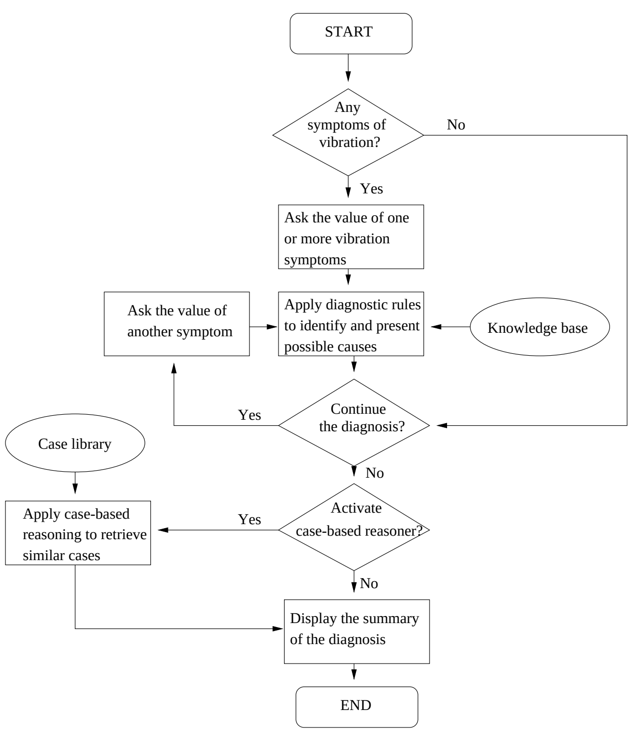

Fig. 3. Core Consultation process of the Integrated System

During a consultation process, the user is asked if any of the basic vibration characteristics are observed from the machine under diagnosis. Given each symptom, the fuzzy rule-based sub-system generates currently possible causes, using the techniques outlined in section II. The user can then decide whether or not to continue the diagnostic process. This decision point has empirically shown to be helpful in diagnosis as the user may already be able to guess what to check given only the partial diagnostic result. When no more symptoms are provided, the system, if required, will activate the case-based reasoning sub-system to improve the accuracy of the final diagnostic findings by applying past cases stored in its case library. Details of the case-based sub-system are given in the next section.

Incidentally, the integrated system also provides a what-if analysis facility (omitted in Fig. 3) to help the user to investigate the impacts of potentially different symptoms upon the diagnostic result. At the end of a consultation, the user is allowed to change any of the given symptoms to see if there are alternative symptoms which may affect the diagnoses significantly. In so doing, the reliability of the diagnoses can be examined and the diagnostic results may be revised (if necessary).

IV. Case-based Reasoning Sub-system

Theoretically, a case-based reasoning system works relying upon the availability of a set of initial cases reflecting the typical relationships between problems and solutions [4]. However, when trying to perform diagnosis on, say, a less experienced type of machine, it may be infeasible to wait until a sufficiently large set of cases have been accumulated. Therefore, the case-based sub-system is herein designed to be able to apply and enrich its case library from experience concurrently.

A. Case representation

In this work, as with any case-based reasoning system, each past case is composed of a problem and its solution, and is stored in the case library. In particular, the solution of a vibration problem refers to a set of underlying causes found (noting that a vibration problem may have more than one cause in real situations). To facilitate case retrieval or similarity assessment (see below), each problem is therefore labelled by a set of indices, which are important features that can be used to characterise the corresponding problem.

For convenience, the symptoms associated with a problem are used to represent the indices. In other words, a case can simply be represented by a set of symptoms and the underlying causes found. Each case is stored in either of the following two forms:

1. $(< case - id >< person >< date >< s_1 >< s_2 > ... < s_n >)$
2. $(< case - id >< person >< date >< c_1 >< c_2 > ... < c_n >< s_1 >< s_2 > ... < s_n >)$

where symptoms $< s_1 >< s_2 > ... < s_n >$ constitute a problem, $< c_1 >< c_2 > ... < c_n >$ constitute its solution, and $< case - id >$ is a unique integer for identifying the case. The other fields in these two representation forms contain additional, potentially useful information. For instance, the field $< person >$ shows the person who was responsible for entering that case. If the solution of this case is found to be appropriate for a new problem, the details of the case such as how to fix the cause may then be obtained from that person.

Given a new problem, the case-based sub-system retrieves similar cases and presents their solutions, often in a modified form, to the user. In order to allow it to collect experienced cases from solving past problems, a new case may be temporarily stored in the first representation form. Once its underlying causes are found and fed back to the system by the user as if the case-based sub-system has successfully learned that piece of experience, the case becomes complete and can then be applied thence. Such cases are then stored in the second form shown above.

B. Case indexing

For the present application, the indices of a problem are conveniently encoded as its associated symptoms and hence, can be denoted by

$$< symptom - name \quad symptom - values >$$

For example, the following list

$$< s_1 \ 4 \ 5 > < s_2 \ 2 > < s_3 \ 4 > < s_4 \ 2 >$$

represents the indices of a case with 4 given symptoms, where, for instance, s_1 represents the observed "predominant frequency of vibration" symptom and the following numbers, 4 and 5, represent its observed values 1xRPM and 2xRPM. Clearly, a symptom may have one or more than one value. The number of indices may also vary from case to case because in real situations, the user may be able to give a particular symptom in describing one problem but not another.

C. Case retrieval

After a new case has been assigned indices, similar old cases, if any, can be retrieved from the case library based on measuring the similarities between their indices and the new case's, using a suitable similarity metric.

Given the indices of a case being directly encoded using symptoms, the similarity between two cases might be measured by using a simple evaluation function defined as the difference between the number of matched symptoms and that of unmatched ones. This might sound good, but it implicitly uses an arguable assumption that a symptom appearing in one case but not the other implies a major difference between the two. However, as indicated in the last sub-section, similar problems may have been assigned a different number of indices. Also, a symptom may have been given a different number of values and these values may be different. In light of this, symptoms that appear in one case but not the other should not be considered when measuring similarity between two cases, whilst the similarity between values of a shared symptom should be taken into consideration.

From the observation above, the following function $S(new, old)$ is designed to measure the similarity between two cases, *new* and *old*, in the present system:

$$S(new, old) = \frac{1}{N} \sum_{i=1}^{N} \frac{2x_i}{2x_i + y_i} \times 100\%$$

where N is the number of symptoms shared by the two cases (i.e., the number of symptoms compared), x_i is the number of matched values in symptom s_i of either of the two cases, and y_i is the total number of unmatched values over symptom s_i of both cases.

To illustrate this, consider a simplified case library consisting of the following three past cases:

a. $< s_1 \ 1 \ 2 \ 3 > < s_2 \ 3 > < s_3 \ 4 \ 5 > < s_4 \ 2 > < s_5 \ 3 >$
b. $< s_1 \ 1 \ 2 \ 5 > < s_2 \ 3 \ 4 > < s_3 \ 4 > < s_4 \ 3 > < s_5 \ 3 >$
c. $< s_1 \ 1 \ 2 \ 3 > < s_2 \ 3 > < s_3 \ 4 > < s_4 \ 2 >$

and the following new case:

$$< s_1 \ 1 \ 2 \ 3 > < s_2 \ 3 > < s_3 \ 4 > < s_4 \ 2 >$$

Using the plausible simple evaluation function, the index s_1 of old case *b* and that of the new case do not match, even though they include two ("1" and "2") of the three values being the same. Using the metric introduced herein, however, the similarities between the new case and the past ones can be evaluated as follows:

Old case *a*: (6/6 + 2/2 + 2/3 + 2/2)/4 = 92%
Old case *b*: (4/6 + 2/3 + 2/2 + 0/2)/4 = 58%
Old case *c*: (6/6 + 2/2 + 2/2 + 2/2)/4 = 100%

It can be seen that old case *c* is found to be exactly the same with the new case (which is exactly the case), and that old case *a* is more similar to the new case than old case *b* (while both have a partial matching). Although this evaluation function provides more accurate similarity measures than the plausible simple evaluation function, the actual similarity between any two cases also depends upon the number of indices or symptoms used. Results generated based on few symptoms seem not to be very unreliable. However, what minimum number of symptoms would lead to reliable results depends on particular application situations. The implementation of the present system is therefore intentionally designed to allow the user to choose this subjectively.

D. Case adaptation

One of the main advantages of case-based reasoning systems, over conventional rule-based approach, is the potential capability of being adapted to new situations. If no past cases are found to match a new situation exactly, the solution of the most similar problem may be modified to suit the new problem according to some domain-specific modification rules.

Although the design of modification rules can be a difficult task, a case adaptation scheme is devised for the present application. Since the solution of a case refers to a set of identified actual causes, the modification of a solution should be an update of this set of causes. This is currently done by removing any causes in the partial solution that are contradictory to the plausible causes generated by firing the diagnostic rules (by the fuzzy rule-based sub-system) which match the given symptoms of that case.

Incidentally, whether the case-based sub-system should work completely independently, without relying upon the diagnostic rules of the rule-based sub-system, may be arguable. Nevertheless, such a complete separation of the two key components of an integrated system is itself fundamentally questionable. Answers to such questions remain as active research.

V. EXPERIMENTAL RESULTS

As with the original fuzzy rule-based system, the integrated diagnostic system is also implemented in FuzzyCLIPS [8]. The results of two typical case studies used in [18] are again utilised here to ease the understanding and comparison. However, to be concise, details (e.g., the incremental diagnostic performance and what-if analysis) of running the fuzzy rule-based sub-system are omitted here, which can be found in [18]. In the following, the first case illustrates in what form the outcomes of a complete consultation of the system may be expected, and the second demonstrates how the case-based reasoning sub-system can provide more reliable diagnoses under complex situations.

Note that the diagnostic system has a threshold for returning ranked possible causes which can be set by the user. This is merely for use in reporting diagnostic results and should not be confused with the threshold of an internal weight for rule firing. Only those causes found whose weights are larger than the set threshold are reported to the user. This facility allows the user to concentrate on important diagnoses only. In both experimental cases below, the threshold is set to 0.5.

A. Case I

The actual underlying cause of this case is “oil whirl” and the symptoms observed are:

(a) predominant frequency of vibration: 40-50% (high)
(b) direction of predominant amplitude: vertical
(c) location of predominant amplitude: shaft
(d) amplitude response to speed increase: coming suddenly
(e) amplitude response to speed decrease: dropping out suddenly
(f) predominant sound of vibration: low frequency rumble

As reported in [18], after all the symptoms available (six observations) have been presented (again, done incrementally) the final result generated by the rule-based sub-system is:

```
  SYMPTOM(S):
  1. Predominant frequency of vibration:
     40-50% oil whirl frequency (high)
  2. Direction of predominant amplitude:
     vertical
  3. Location of predominant amplitude:
     shaft
  4. Amplitude response to speed increase:
     coming suddenly
  5. Amplitude response to speed decrease:
     dropping out suddenly
  6. Predominant sound of vibration:
     low frequency rumble
POSSIBLE CAUSE(S):
  1. bearing and support excited vibration (oil
     whirls, etc.) (1.0)
  2. thrust bearing damage (0.99)
  3. casing distortion (temporary) (0.97)
  4. rotor rub axial (0.94)
  5. bearing damage (0.93)
  6. seal rub (0.87)
  7. piping forces (0.82)
>> Do you want to perform what-if analysis on
>> the result?
yes/no:
```

When the rule-based consultation is finished, the case-based sub-system can be invoked to retrieve similar cases (generally, in order to refine the diagnoses, see the next sub-section). For the present example problem case, applying the case-based reasoning results in the following:

```
  According to my past experience, the
following previous cases are found to be
similar with your current case:
  ID: 2, Date: 12 Aug 96, Responsible: Donald,
Similarity = 16.67%
journal and bearing eccentricity
  ID: 3, Date: 1 Sept 96, Responsible: Donald,
Similarity = 16.67%
temporary rotor bow
  ID: 4, Date: 15 Aug 96, Responsible: Donald,
Similarity = 16.67%
permanent bow or lost rotor parts
>> These cases may be useful if similar
>> problems occur. So, do you want me to
>> remember them?
yes/no:
```

In general, a case-based reasoning system retrieves only the most similar case(s) only. In this work, the user is allowed to look at cases with a varying similarity (by changing system’s setting for the least similarity level of interest). Unfortunately, due to the use of an initially poor case library for this real application, the three “matched” cases all have a low similarity degree and hence are not very useful. However, once the underlying cause of the problem is found it can be fed back to the system by the user to enrich the case library for future use. This feature allows the case-based sub-system and therefore, the overall diagnostic system to be adapted from actual experience.

B. Case II

In this case, the actual underlying cause is “thrust bearing damage”, and the symptoms observed are:

(a) predominant frequency of vibration: 1xRPM (high) and 2xRPM (high)
(b) direction of predominant amplitude: horizontal
(c) location of predominant amplitude: shaft
(d) amplitude response to speed increase: increase
(e) amplitude response to speed decrease: decrease
(f) predominant sound of vibration: loud roar

After presenting all of the observed symptoms one by one, the final diagnostic result produced by the rule-based sub-system is:

```
  SYMPTOM(S):
  1. Predominant frequency of vibration:
     1xRPM (high), 2xRPM (high)
  2. Direction of predominant amplitude:
     horizontal
  3. Location of predominant amplitude:
     shaft
  4. Amplitude response to speed increase:
     increases
  5. Amplitude response to speed decrease:
     decreases
  6. Predominant sound of vibration:
     loud roar
POSSIBLE CAUSE(S):
  1. thrust bearing damage (1.0)
  2. journal and bearing eccentricity (1.0)
  3. foundation distortion (1.0)
  4. casing distortion (permanent) (1.0)
  5. casing distortion (temporary) (1.0)
  6. temporary rotor bow (1.0)
  7. permanent bow or lost rotor parts (1.0)
  8. initial unbalance (1.0)
  9. bearing damage (0.99)
 10. seal rub (0.99)
 11. piping forces (0.98)
 12. misalignment (0.98)
 13. rotor rub. axial (0.98)
>> Do you want to perform what-if analysis on
>> the result?
yes/no:
```

In this case, the fuzzy rule-based sub-system identifies 13 possible causes, each having a very high significance weight. Although the actual cause “thrust bearing damage” is ranked the top, there are 7 other causes also found to have the maximum possibility of 1. Albeit multiple causes for vibration may be common in rotating machines, there would not normally exist so many of them at the same time. Fortunately, the case-based reasoning sub-system provides a more accurate diagnosis as shown below:

```
  According to my past experience, the
following previous cases are found to be
similar with your current case:
  ID: 2, Date: 12 Aug 96, Responsible: Donald,
Similarity = 50.0%
journal and bearing eccentricity
  ID: 3, Date: 1 Sept 96, Responsible: Donald,
Similarity = 61.11%
temporary rotor bow
  ID: 4, Date: 15 Aug 96, Responsible: Donald,
Similarity = 66.67%
permanent bow or lost rotor parts
  ID: 5, Date: 20 Aug 96, Responsible: Donald,
Similarity = 100.0%
thrust bearing damage
>> These cases may be useful if similar
>> problems occur. So, do you want me to
>> remember them?
yes/no:
```

As can be seen, four similar cases are retrieved from the case library. In particular, past case number 5 has a similarity of 100% with the current case. This means that old case 5 has exactly the same symptoms as the current case. This reinforces the finding of the fuzzy rule-based sub-system in that it is very likely that the underlying cause in old case 5, i.e. “thrust bearing damage”, is the cause of the current problem. Therefore, while the rule-based sub-system can postulate possible causes of a vibration problem, the case-based sub-system may provide more useful information for the user to discriminate between potentially multiple diagnoses and to decide what to check next. This helps minimise the significant limitation of the original fuzzy rule-based diagnostic system in potentially returning a large number of possible faults, through maximising the use of past experience.

VI. CONCLUSIONS AND FURTHER WORK

This paper has presented an integrated knowledge-based system for turbomachinery diagnosis. The work is based on the most recent development in performing monitoring and diagnosis using fuzzy systems technology, as reported in [18]. According to the experimental results obtained so far, the fuzzy rule-based sub-system can identify the underlying cause(s) of a real problem and the case-based sub-system can provide useful and reliable information to refine the outcomes of rule-based diagnosis.

Whilst the overall system seems to work well in an effort to help finding faults of experienced nature, it is not expected for it to work equally well for situations where unseen faults may occur. As with the original fuzzy rule-based system, the current approach relies upon the assumption that a full coverage of symptom-cause associations can be extracted from Sohre’s charts. Although this may be the case for commonly applied rotating machines, knowledge regarding certain new types of machine may not be complete. To address this important issue, work is ongoing to investigate the possibility of applying qualitative model-based reasoning, as per the Tiger system that is presented in [13]. This is because model-based reasoning systems have the inherent ability of being adaptable to coping with problems previously unforeseen [6].

In addition, as there exist many alternative approaches to similarity measurement which plays a central role in case-based reasoning, further work will be carried out to examine the effects of applying different similarity metrics for case retrieval.

Finally, as indicated previously, it is interesting to investigate whether the case-based reasoning sub-system has to be completely separated from the rule-based sub-system. A more interconnected structure of the overall diagnostic system may help improve the diagnostic efficacy. For example, in order to enhance diagnostic accuracy and speed, the cases in the case library may be fuzzified and grouped into several clusters in advance [5]. When a new case occurs, the integrated system will find the closest group for the new case. Then the new case will be matched, using the fuzzy matching technique, only against cases in the closest group. Alternatively, case-based reasoning may be used to act as the principal inference mechanism of the system, with cases’ representation, including variables’ description, and similarity measures implemented in a fuzzy manner. The work most recently proposed in [2] seems to benefit from this approach. Such investigations remain as active research.

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